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Railway transportation efficiency improvement: loco health assessment by time domain data analysis to support Condition Based Maintenance implementation

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Abstract

Health estimate of loco mechanical transmission components usually implies the on-board installation of fit-to-purpose devices and the use of specific protocols for data acquisition. In this paper the authors present a different approach, based on the acquisition and post-processing of the stator currents of an induction traction motor, easy to be measured and already monitored by standard on-board automation systems. The use of a PWM inverter for the electrical drive of the traction unit introduces harmonics in the stator currents, and an analogous effect is due to the presence, for instance, of a bearing fault. For this reason, the authors have paid great attention to the choice of a reliable de-noising technique for the removal of the harmonic content due to the electronic conversion unit. The so cleaned stator current time series have been then processed by the Independent Component Analysis (ICA) method, in order to identify some current "features" able to predict motor condition. On the basis of a huge amount of data deriving from a laboratory test campaign, the author present and discuss in the paper the results of their study.

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Keywords: Condition Based Maintenance; Inverter-fed induction motor; Diagnostics; Independent Component Analysis

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1. Introduction

In the railway transportation field, as it happens for the whole industrial world, the run-up to the operating costs reduction and the growing need for environmental sustainability are radically changing the management and maintenance philosophy of logistical infrastructures and vehicles.

In such a context, the improvement of techniques devoted to health status monitoring of electrical machines and their components becomes therefore essential to maximize the operational life of the vehicle, avoiding unavailability periods due to unnecessary maintenance, without compromising safety standards for goods and travelers.

To this aim the conventional fixed time interval maintenance procedure, depending on item mileage or hours of operation, could be effectively substituted by, or integrated with, new methods or criteria based on the actual conditions of components and subsystems, hence the term Condition Based Maintenance (CBM). Obviously, the mentioned approach is applicable just for items (typically mechanical or electro-mechanical macro-components) whose performance deterioration may be detected during the life period by measuring suitable physical quantities. The implementation of such an innovative approach mandatorily implies, for the particular application, the need of a "continuous" monitoring of the health status of on-board equipment, but CBM procedure can also greatly benefit from laboratory test results aimed at the creation of an historical database before operation.

Another great advantage of a preliminary test campaign on some items from a particular components family is the possibility to estimate, as far as CBM criteria application is concerned, the effectiveness of monitoring different parameters and to choose the solution that minimize the required workload and costs for on-board already existing equipment (in terms, for instance, of sensors installation). If a loco is taken into account, traction chain mechanical components (bearings) represent an example of the previously mentioned statement.

Thanks to a wide laboratory (destructive) test campaign carried out on a real loco traction chain, the authors have analyzed collected data to understand if stator current can be a significant indicator to define health status of mechanical transmission components.

Stator current measurement and analysis are often used to support diagnostic techniques as they allow fault detection without requiring direct access to the device (Benbouzid, 2000; Kliman et al., 2011). For such an equipment broken rotor bars and bearings faults are two main types of defects and most of the research activities have been carried out by decomposing and analyzing the stator current by various methods, such as Fourier analysis, Wawelet analysis, neural networks methods, model-based techniques or other statistical analysis (Yazici et al., 1999; Schoen et al., 1997; Ayhan et al., 2005; Su et al., 2007; Ayhan et al., 2006).

The Independent Component Analysis (ICA) is a relatively new method for separating a multivariate signal into additive subcomponents supposing the mutual statistical independence of the non-Gaussian source signals (Hyvarinen, 1999). A wide literature is available to testify the effectiveness of the use of such a method for many applications, such as image processing (Lee et al., 2002; Barlett et al., 2002), biomedical engineering (Semmlow et al., 2002) and load prevision of power systems (Liao et al., 2003), but just a limited number of scientific papers deal with the application of ICA for the fault detection in induction motors. These applications look at limited power devices in quasi-stationary fault conditions, due to the economic difficulties in carrying out experimental procedures for medium/big size motors over a not negligible time window.

Aim of the paper is to exploit the potentialities of ICA in extracting the intrinsic features of stator current signals of a medium size motor in bearings growing fault conditions. Due to the non-stationarity of the damage this approach could represent an effective diagnostic method for Condition Based Maintenance applications.

Being the induction motor tested part of a loco traction chain, the current signal is always corrupted by noise originated from the electronic components switching of the inverter feeding the electrical machine. Such noise may cause uncertainty when discriminating between the healthy bearing pattern and the faulty unit signals (Akin et al., 2008). Due to the random nature of stator current noise from the inverter-fed motor, a noise reduction algorithm has been employed.

The present paper is divided into four parts that reflect the various steps of the performed activities. In paragraph 2 the ICA algorithm utilized by the authors for the determination of the independent component features is shown, while in paragraph 3 the chosen method for random noise reduction is summarily described. Finally, paragraph 4 reports the main information about the experimental setup and paragraph 5 presents results and conclusions of the study.

Nomenclature

H	differential entropy
J	negentropy
IC	independent component

2. Principles of ICA

Independent Component Analysis (ICA) is a statistical method for decomposing an observed complex dataset into components as much as possible statistically independent from each other. In other words, ICA is a method that represents a multidimensional random vector as a linear combination of non-gaussian random variables, called independent components.

The problem is to determine a constant transformation matrix A so that the linear transformation of the observed variable

$$x = A \cdot s \tag{1}$$

is characterized by a set of suitable properties, as described in the following. In (1) $x = (x_1, x_2,..., x_m)^T$ is an observed m-dimensional random vector and $s = (s_1, s_2,..., s_n)^T$ is an n-dimensional random vector, whose components are assumed mutually independent. A is a constant m x n matrix. Usually the dimensions of x and s are equal ($m = n$).

One possible ICA application deals with Feature Extraction and the present study belongs to this category of problems. In Feature Extraction s_i becomes the coefficient of the i^{th} feature in the observed data vector x. In such a context, the effectiveness of ICA is motivated by results gained in neurosciences filed and it this procedure has been also applied in exploratory data analysis with outcomes as satisfactory as the ones achievable by the closely related Projection Pursuit method.

The algorithm usually adopted for estimating A is the fixed-point FastICA calculating the independent components one-by-one like in Projection Pursuit (Hyvarinen, 1999).

2.1. Identification of Independent Components and Feature Extraction

Some authors have demonstrated that a general formulation for ICA that does not need an underlying data model is based on the concept of mutual information (Hyvarinen, 1999).

Defining $H(y)$ the differential entropy of a random vector $y = (y_1, y_2,..., y_n)^T$, characterized by a probability density function $f(y)$, as it follows:

$$H(y) = -\int f(y) \log f(y) dy \tag{2}$$

it is possible to introduce the concept of negentropy $J(y)$:

$$J(y) = H(y_{Gauss}) - H(y) \tag{3}$$

where y_{Gauss} is a random Gaussian variable having the same covariance matrix as y. Negentropy can also be viewed as a measure of non-gaussianity and has the property of being invariant for linear transformations.

Finally, by differential entropy concept it is also possible to introduce the mutual information function I, that represents one possible measure of the mutual dependence among n (scalar) random variables y_i ($i = 1,....,n$). Expressing mutual information I through negentropy (constraining the variables to be uncorrelated):

$$I(y_1, y_2, ..., y_n) = J(y) - \Sigma_i J(y_i) \tag{4}$$

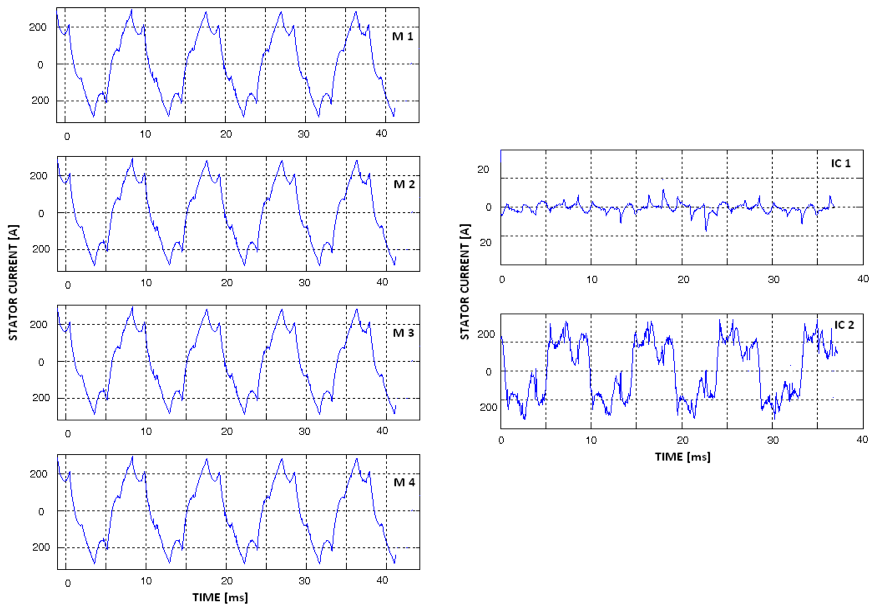


Fig. 1. Example of measured signals (left) and independent components (right).

Being function I the information-theoretic measure of the independence of random variables, it is possible to use it as the criterion for finding the ICA transform.

Considering (1), A will be determined so that the mutual information of the transformed components s_i is minimized.

Since negentropy is invariant in invertible linear transformations, an invertible transformation that minimizes the mutual information is roughly equivalent to finding directions in which the negentropy is maximized. This approach shows the connection between Projection Pursuit and ICA in finding a single direction that maximizes negentropy, and could also be interpreted as estimation of each single independent component.

Just as an example, on the left side of Fig. 1 the behavior of a subset of the signals (induction motor stator currents) processed by the authors is shown. Each signal Mi (i = 1 ,…, 4) corresponds to a different level of bearing degradation (M1 identifies the healthy item) and consists of 800 elements. For the purposes of the present study it has been necessary to reduce the number of measured signals to better improve the efficiency of classification without decreasing the discriminating power of the original signals.

In order to decrease the complexity of the problem, just two independent components have been identified by the deflation criteria algorithm, able to estimate independent components one by one as in Projection Pursuit. All the measured signals are so reduced into a smaller working data set (Wang et al., 2009), by projecting them into the two (most dominating) independent components thanks to the following equation:

$$IC = M \cdot ICA^T \tag{5}$$

where IC is a m x n matrix of the independent component features of the N signals, M is a m x p matrix of the measured signal and ICA is a n x p matrix of the most dominating independent components.

Finally, m = 1 ,..., N, n = 1, 2 and p represents the number of records for each measured signal. The results of such approach are depicted on the right side of Fig. 1 for the example previously mentioned.

3. Noise reduction

Stator current harmonics introduced by the switching phenomena of PWM inverter tend to overlap the ones produced, for instance, by a bearing mechanical fault. As technical and scientific literature clearly testifies, traditional techniques, such as the Fast Fourier Transform or the Wavelet Analysis, aimed at detecting bearing failure through analysis of stator currents in the frequency domain, are often not sufficiently reliable.

For this reason, the authors have paid great attention to the development of an efficient algorithm for the removal of current harmonic content (noise) due to PWM inverter in data post-processing phase. In particular, the effectiveness of two algorithms has been preliminarily tested and the outcomes compared: the first algorithm implements the conventional release of the Averaging Method de-noising technique, while the second represents a variant called Ensemble and Individual Noise Reduction Method (EINR) (Chua et al., 2010; Wang et al., 2009). To the purpose of this study, the authors have chosen the second option, showing great potentialities in the case of inverter fed motors.

In particular, it seems to be particularly effective in diagnostic procedures carried out in the time domain by statistical methods, as it allows to maintain as much as possible the characteristics of each record, limiting the attenuation phenomena proper of averaging algorithms.

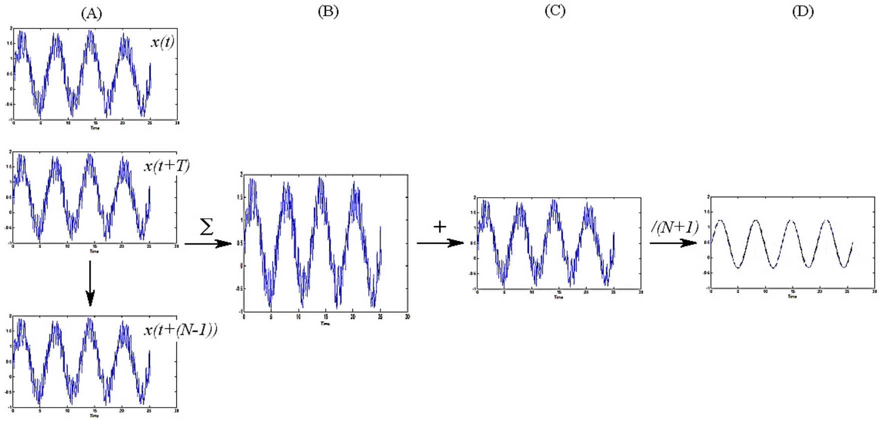


Fig. 2. EINR method: measured noisy signals (A) – $P(t)$ (B) – $y(t)$ (C) – De-noised signal y_D (D).

A schematic representation of EINR is shown in Fig. 2. Due to the random nature of the noise caused by switching events inside the inverter, it is possible to reduce it by averaging a predetermined number of corrupted signals. Indicating by $x(t)$, $x(t+T)$, ... , $x(t+(N-1)T)$ a set of aligned periodic noisy base signals from the same source (where T is the signal time window and N is the signals number), the first step is to compute the profile signal $P(t)$ which is the summation of all the noisy base signals:

$$P(t) = \sum_{K=0}^{N-1} x(t + kT) \tag{6}$$

Thanks to the intrinsic potentialities of the averaging methods in general, in this first step most of the noise has been eliminated in the signal profile. To improve noise reduction EINR foresees a further step, where it is possible to calculate the de-noised signal $y_D(t)$ for any new incoming noisy signal $y(t)$ maintaining memory of the previous acquisitions by the following equation:

$$y_D(t) = (P(t) + y(t)) / (N+1) \tag{7}$$

At last, it is worth mentioning that EINR method is characterized by performances similar to the ones of other averaging methods, with the need of a reduced number of acquisitions. Such advantage is not negligible whenever it is necessary to obtain a de-noised signal without the availability of a huge set of data and can turn out useful for on-line applications concerning, for instance, railway locos in real operating conditions.

4. Experiment setup

In Fig. 3 a schematic representation of the test bench is shown. It is a full scale model of a real traction chain made for laboratory multiple measurements, powered by a loco PWM inverter. The mentioned chain is composed of a traction three-phase induction motor (nominal power 500 kW) connected to an identical equipment, acting as an electrical brake, by a single stage gearbox.

The described system is equipped with two accelerometers (one on the motor and one on the gearbox) and a measurement and recording system for stator current acquisition, installed for one phase only.

In order to speed up the wear-out process of the traction chain mechanical items some defects have been artificially injected into the motor bearing (spalling on the rings and on the rolling surface). Spalling dimension has been chosen small enough to avoid a rapid failure of the mechanism.

Bearing damages have been constantly monitored with accurate visual inspections in order to check the real status of the whole mechanism and the evolution of the artificial damage. During those operations normal signs of wear-out (such as dark lines or indentations) have been also found on the two faced shaft bearings of the traction motor and of the gearbox. These defects were classified as "natural defects".

Measurements have been carried out over several months and during this time interval the system has continuously operated under the laboratory technicians supervision. Both acceleration and stator current have been measured at different sampling frequencies: during each acquisition, accelerations have been acquired for few seconds with a sampling frequency of 100 kHz, while stator current has been acquired for approximately 30 s with a sampling frequency of 20 kHz.

Acceleration measurement has been performed to associate each stator current acquisition to the real conditions of the mechanical equipment, being the goal of the study to demonstrate that by applying EINR and ICA algorithms on stator current analysis it is possible to detect, for instance, bearing degraded conditions.

Vibration measurements are also essential to establish alarm thresholds in a Condition Based Maintenance context. Once verified the effectiveness of the proposed approach, these thresholds should be suitably processed (translated) to identify analogous constraints on the corresponding independent component features obtained by stator current analysis. In Fig. 4 a possible structure of the diagnostic process flow for the implementation of a CBM strategy is presented.

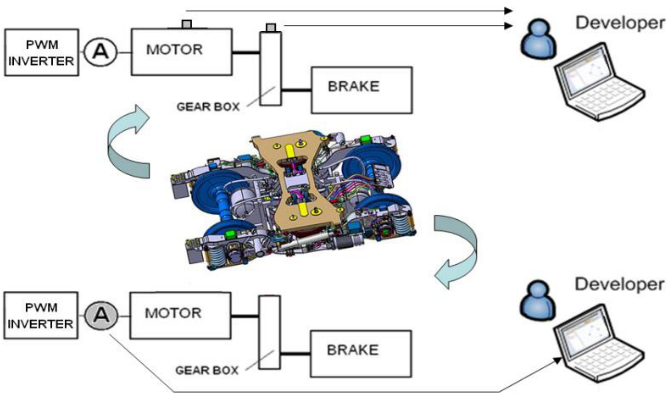


Fig. 3. Schematic test bench: acceleration acquisition (above) – stator current measurement (below)

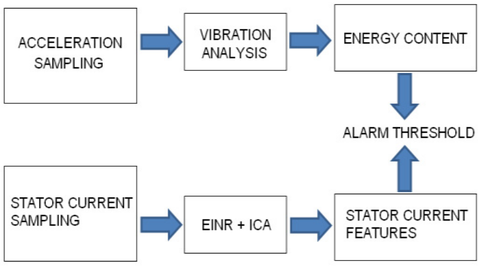


Fig. 4. Diagnostic process flow (threshold identification – CBM approach)

5. Results and conclusion

In this section the authors present the results of post-processing activities developed on stator current records to demonstrate that, through the combined use of EINR and ICA algorithms, it is possible to identify mechanical components degradation, as well as to reduce the large amount of stored information without losing valuable information about the phenomena under study. Data analysis has been carried out in Matlab®.

5.1. De-noising process

As previously mentioned, each stator current acquisition has been performed at regular intervals along the experimentation period, for a time window of 30 s at a sampling frequency of 20 kHz. As a consequence, the related vector is composed of $6 \cdot 10^5$ elements.

Using the notation of paragraph 3, each $x(t)$ gives rise to a vector of 800 elements. Just one $x(t)$, typically the first, is used as the main acquisition vector while the remaining 749 compose $P(t)$ according to (6). The de-noised signal $y_D(t)$ is then obtained according to (7). In this way each current acquisition is reduced to a vector of 800 elements.

On the basis of these calculations it is possible to verify how the combination of all the vectors $y_D(t)$ produces, according to (5), a matrix M having size 50 x 800, being 50 the number of acquisitions.

In order to show that noise reduction is one of the mandatory activities to be carried out for exploiting ICA method effectiveness, stator current acquisitions have been processed with and without the described EINR algorithm. The outcomes of such analysis are presented in the following Fig. 5.

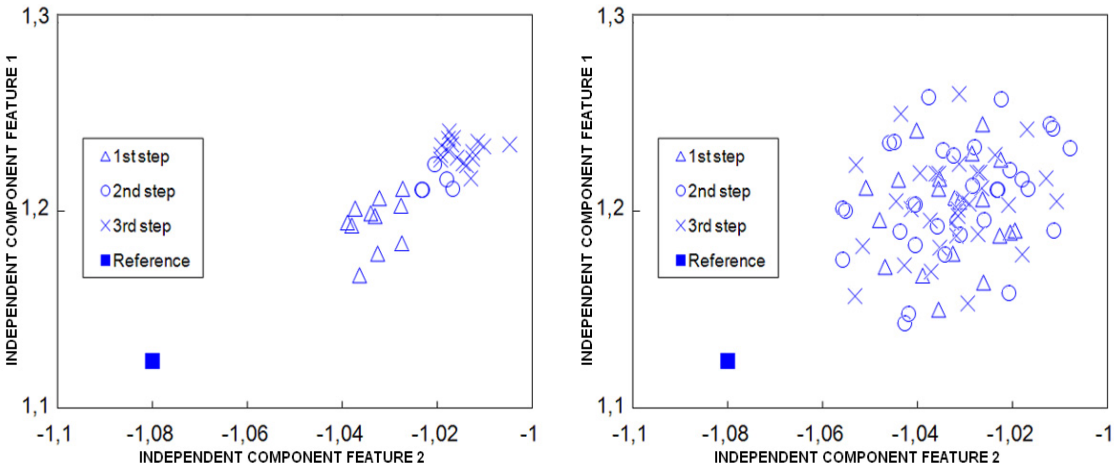


Fig 5. Faulty and Healthy signatures: noise reduction on (left) – noise reduction off (right)

5.2. Data set reduction and feature calculation by ICA

According to the criteria reported in (4), it is possible to determine *ICA* matrix, whose dimensions are, in general, 800 x *D*, being *D* the number of the selected independent components. Since it is necessary to represent the independent component features *IC* by equation (5) in a two-dimensional space, *D* = 2 has been assumed, limiting ICA algorithm to the extraction of the first and the second component. As a consequence, *IC* turns out a 50 x 2 matrix, whose elements are plotted in Fig. 5.

For a better reading, it is worth mentioning that the experimentation overall time horizon has been suitably subdivided into four different intervals, each related to a well defined degradation status. In particular, the first interval refers to the healthy bearing (reference), while the others three to growing wear-out conditions (step 1 to 3).

At last, due to the negligible numerical differences among some stator current acquisitions, an almost complete overlap of the graphical points representing relevant independent component features sometimes turn out.

5.3. Conclusions

Thanks to the results depicted in the left side of Fig. 5 it is possible to verify that points are rather orderly distributed in time and, as a consequence, according to the bearing actual deterioration. This preliminary analysis confirms the effectiveness of the approach, as far as potentialities in detecting degraded conditions are concerned.

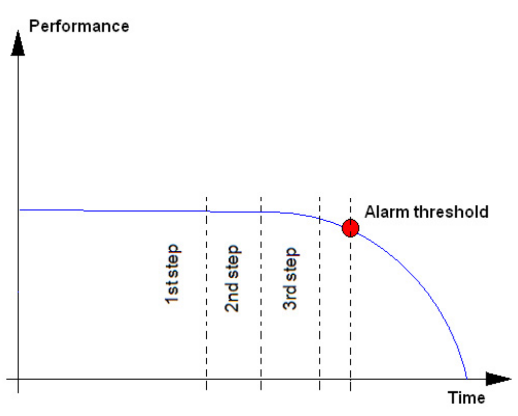
Moreover, a comparison between the results presented in the two diagrams of Fig. 5 confirms the need for the application of a preliminary de-noising technique.

Results also testify the possibility to utilize the method for monitoring deterioration trend. In such a context, it is worth noting that the clear difference among the points identifying the reference case and the remaining (degraded) features is due to the fact that, in addition to natural wear, others defects have been artificially introduced causing discontinuities inside the system evolution.

Vibration analysis, based on the classical technique of exploring defect characteristic frequencies for the bearing, has shown an analogous clear tendency of the defect evolution.

On the basis of the achieved results, it is possible to assess that the combination of an effective noise reduction method and ICA technique can provide useful information about evolving degradation phenomena, starting from the early phase of the deterioration process.

Referring to the curve presented in the left side of Fig. 6, the usual behavior of the performance indicator of a mechanical device versus time gracefully decreases up to the minimum allowed value (alarm threshold), before dropping toward final collapse (null performance). The assumption of linearity made for implementing ICA



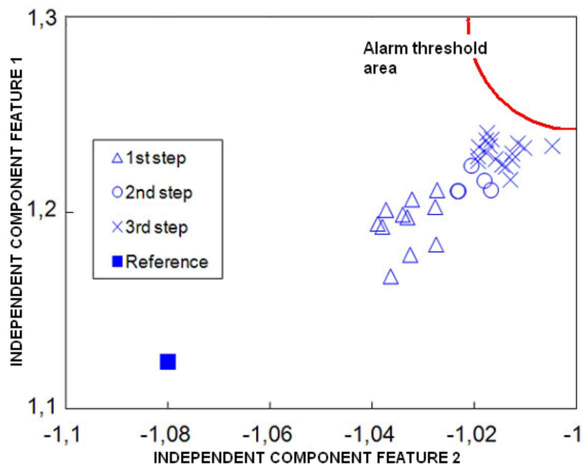


Fig. 6. Faulty and healthy signatures in comparison with a typical performance diagram

approach and expressed by equation (1) is therefore quite compatible with gracefully degrading systems, as the case study analyzed in the paper. To utilize diagnostic capabilities of the methodology proposed by the authors for implementing a CBM approach, the threshold alarm should be suitably translated in the independent component space, identifying an alarm area qualitatively shown in the left side of Fig. 6.

Finally, to further test the reliability of the method, it will be necessary to investigate the behavior of the algorithms taking into account different load conditions (motor torque variation, with consequent variation of the RMS value of the current) and the increase of bearing degradation behind the alarm threshold. These two additional aspects will be object of future research activities.

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